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A Forward-Looking Ricardian Approach: Do land markets capitalize climate change forecasts?[☆]

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ABSTRACT

The hedonic pricing method is one of the main approaches used to estimate the economic value of attributes that affect the market price of an asset. This method is routinely used in environmental economics to derive the economic valuation of environmental attributes such as air pollution and water quality. For example, the "Ricardian approach" is based on a hedonic regression of land values on historical climate variables. Forecasts of future climate can then be employed to estimate the future costs of climate change. We show that this approach is only valid if current land markets ignore climate forecasts. While this assumption was defensible decades ago (when this literature first emerged), it is reasonable to hypothesize that information on climate change is so pervasive today that markets may already price in expectations of future climate change. Indeed, we show empirically that agricultural land markets in the United States now capitalize expectations about future climate change. We derive a straightforward empirical correction to the standard Ricardian approach (called the "Forward-Looking Ricardian Approach") that can be implemented with readily available data. Accounting for market beliefs decreases the estimated magnitude of climate change damages by 50%–62%.

1. Introduction

One of the greatest contributions of applied econometrics has been to provide empirical methods for estimating the economic consequences of anticipated future changes. The canonical application centers around the estimation of cross-sectional hedonic regressions using market outcome data to estimate the response of asset prices to exogenous variation in a variable of interest and that is expected to change in the future (due to change in policy, regulations, or other factors).[1] With the esti-

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[1] Most empirical applications build on the seminal work of Rosen (1974) and derive estimates of household willingness to pay for an array non-market amenities.

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mated relationship in hand, it is straightforward to predict the costs or benefits associated with expected future changes in any variable of interest, i.e. to project the expected change in the state variable on the empirically estimated price gradient. This broad approach has been used in prominent papers to value potential future regulatory changes to the Clean Air Act (Chay and Greenstone, 2005), policies that are expected to reduce crime rates (Linden and Rockoff, 2008), and policies that are expected to improve local school quality (Black, 1999), among numerous others.

One branch of this literature that has had a tremendous policy impact focuses on the economic consequences of climate change. In that context, the method is known as the Ricardian approach, following the seminal paper of Mendelsohn et al. (1994) (hereafter MNS). The key empirical component of the Ricardian approach is a cross-sectional regression of land values on historical climate conditions and other relevant variables to estimate how the value of an asset (a parcel of land) is affected by climate.[2] The analyst then uses the estimated climate-price gradient along with scientific predictions of future changes in temperature and precipitation (and possibly other climate variables) to estimate the economic impact of climate change.

These hedonic analyses contain an important implicit assumption that economic assets do not already capitalize the future change that is now anticipated by the researcher. In the climate change example, this amounts to assuming that current land markets fail to account for climate change forecasts. While this was quite plausible for land market data in the 1980s and 1990s, it is reasonable to wonder whether that is still the case today.

If land markets already capitalize available information on climate change, the standard Ricardian approach may be severely biased. When a valuation method relies on asset markets, it must consider the fact that current asset prices rationally account for expected future changes in all relevant variables that determine its value (e.g., the state variables). As we show, ignoring the forward-looking nature of asset markets leads to a misspecified empirical regression model, biased estimates of the price gradients for the relevant state variables, and ultimately biased predictions regarding the economic effects of the anticipated future changes in the state variables. We illustrate these issues in the context of the Ricardian approach and argue that future applications of the method must be modified to account for the simple, yet powerful, fact that asset markets capitalize information. Put simply, because climate information is so pervasive, current land prices should reflect expected future climate, not just the currently observed climate.

Our review of the literature indicates that existing theoretical presentations and empirical implementations of the Ricardian approach indeed implicitly assume that the current asset market ignores possible future change in the climate or other state variables. We label those applications the *myopic* Ricardian approach. We show that this critique applies generally, except when either (1) the market does not capitalize any expectation of future change in climate or other determinants of land value, or (2) an unlikely technical condition wherein the product of the correlation between current and future climate and the ratio of their standard deviations is precisely equal to one.

This paper makes several contributions. First, we present a simple model of asset valuation that allows for market capitalization of information about future state variables to show that asset values should reflect expected future changes in the state variables. When applied to the Ricardian context of land values and climate, our model shows that observed land values should reflect expected *future* climate variables. This is in sharp contrast with current applications of the Ricardian method, which rely on regressions of land values on observed *historical* climate variables.[3]

Second, we derive conditions under which the bias occurs for two related misspecifications of the pricing equation. The first misspecification retains the dynamic structure of the pricing process. The second corresponds to the approach of much of the Ricardian literature, and is entirely static. We describe the theoretical direction of these biases and the factors that lead them to have a large or small magnitude. The direction and magnitude of these biases hinge on the correlation between past and future states and on the variances of those states (climate in our example) and can generally be positive, negative, or zero. Bias is likely to occur anytime that climate change is expected to cause different changes in different places.

Third, we derive a flexible, straightforward correction that can be implemented with readily available data and can accommodate a degree of uncertainty as to precisely what information the market regards as the forecast. This approach accounts for market information, the timing of information acquisition, the stream of revenues associated with various state variables, and the possible divergence of information between the market and the analyst. Without such a correction, the myopic Ricardian method generally leads to biased estimates of the relationship between climate and land values, and thus biased predictions about the future economic consequences of climate change.

Finally, we apply the proposed forward-looking Ricardian regression and find clear evidence that land markets already capitalize climate forecasts. This suggests that existing estimates of climate change impacts in the literature reflect the bias created by using the myopic Ricardian model. This bias is economically important: accounting for current market information about future climate change decreases estimates of climate change damages by 50%–62%, depending on the assumption about the

[2] The Ricardian regression specification typically includes historical average precipitation and historical average temperature. For illustrative power, our theoretical exposition focuses on a single climate variable: average temperature. The critique we present in this paper applies to other climate variables that enter the land pricing equation, such as precipitation, and are accounted for in our empirical work. Deschênes and Greenstone (2007) and Massetti and Mendelsohn (2011) have extended the cross-sectional Ricardian method to the panel data framework.

[3] A recent search revealed that MNS has been cited in >1300 publications on Google Scholar and has been used to examine the effects of climate change in various contexts; none of the most cited papers incorporate information. The Ricardian method has been used broadly to look at the agricultural effects of climate change worldwide: in Africa (Kurukulasuriya et al., 2006; Seo and Mendelsohn, 2008b), in Asia (Seo et al., 2005; Liu et al., 2004; Chang, 2002), in South America (Seo and Mendelsohn, 2008a), and in Europe (Madison, 2000; Reidsma et al., 2007). These, and Ricardian studies in general, either utilize the value of agricultural production directly or as estimated from the value of agricultural land. Our critique is most relevant when these estimates rely on land values, but apply anytime information may play a role in asset price formation.

model of future climate trajectory. We provide two pieces of supporting evidence. Using a new county-level data set on perceptions over climate change from Howe et al. (2015), we find that land values are more strongly related to future climate predictions (as opposed to past climate normals) in counties with higher beliefs in climate change. We also show that land values in recent years follow future climate predictions more closely than in the 1970s and 1980s.

2. The role of information in the Ricardian literature

In a competitive setting, rational agents with well-defined property rights price assets to reflect the expected stream of rents generated from the asset. In non-commodity markets, variation in the characteristics of an asset determines the market valuation of the asset and thus the price at which similar assets are sold. A large literature utilizes this sort of variation to estimate the willingness to pay for a wide variety of non-transacted goods. In hedonic valuation we use market data to determine the otherwise unobservable preferences on packages of characteristics for non-transacted goods (Rosen, 1974). This methodology has been extensively used to estimate the economic value of climate and other non-transacted amenities in land and housing markets (Albouy et al., 2016; Blomquist et al., 1988; Cragg and Kahn, 1997; Roback, 1982; Sinha and Cropper, 2013).

The hedonic method has also been applied widely to study the effect of various climate amenities on agricultural land prices. By estimating these effects, the monetary impact of changes in future amenity (climate) levels can be estimated. By assuming that farmers are profit maximizing and so adjust farming decisions in response to shifts in amenity levels, the hedonic method recalls David Ricardo's seminal work and is commonly referred to as the Ricardian method. This method, first proposed in MNS, is based on a cross-sectional regression of land values on a variety of historical climate variables (such as average temperature and precipitation) and interprets the results as the effect of these variables on agricultural productivity. The impact of climate change is calculated by taking the linear combination of these regression coefficients and predicted (rather than historical) future climate. MNS concluded that a uniform 5° change in temperature and 8% increase in precipitation leads to between a 4–5% loss and a 1% gain in farmland values (a loss of \$6–8 billion per year to a gain of \$1–2 billion per year, based on 1982 revenue).[4]

The hedonic approach in this context can be sensitive to specification, potentially indicating misspecification or omitted variables. Deschênes and Greenstone (2007, 2012) analyze the question of climate change's effect on US agriculture in a different manner, using annual variation in temperature to identify a lower bound on the effect of climate change. They conclude that climate change will lead to a reduction of agricultural profits of \$4.5 billion per year (in 2002 dollars) by the end of the century.

While asset markets generally capitalize the expected future levels of relevant state variables, the timing at which information about future changes is absorbed by the market is critical. In the context of global climate change, the accumulation and dissemination of evidence regarding the predicted rise in temperatures began in the 1990s. For example, the IPCC's First Assessment Report was published in 1990 and predicted an increase in global mean temperature of about 0.3 Celsius per decade. Thus, land value data from the preceding decades are unlikely to reflect future climate change. As public knowledge about climate change advanced over the 1990s and 2000s, it is reasonable to wonder whether these anticipated impacts are reflected in current land values.[5] This is the key premise underlying this paper.

In Ricardian studies that use the US Census of Agriculture (Mendelsohn et al., 1994; Schlenker et al., 2005, 2006; Deschênes and Greenstone, 2007), the value of agricultural land is farmers' (self-reported) estimate of the market value of the land. This value capitalizes information about future market conditions. The intuition underlying this is straightforward: suppose it is well known that a parcel of farmland will experience a large exogenous decrease in soil quality the year after a proposed sale. Its value in a market with symmetric information would be lower than an otherwise equivalent parcel with constant soil quality. Failure to incorporate information into the hedonic model amounts to an implicit assumption that market participants use only historic information to predict the future value of an asset. In the Ricardian literature, this is akin to assuming that farmers (or any participant in land markets) ignore predictions about future climate; this seems inconsistent with other assumptions in the Ricardian model that farmers are sophisticated profit maximizers.

The economics literature has consistently shown that agents adjust their behavior based on environmental forecasts; recent examples include Rosenzweig and Udry (2013) and Shrader (2017). A recent empirical literature has begun to address and model the role of expectations related to environmental risks, generally by finding proxies for the probability that some uncertain (binary) event will occur. These proxies serve to approximate consumer or market perception of risk. Meng (2017) uses prediction market prices to capture market beliefs relating to the risk of climate regulation in order estimate the cost to firms of climate change legislation. Gallagher (2014) models learning about uncertain, infrequent flooding events in the United States. Davis (2004) finds the marginal willingness to pay to avoid the risk of pediatric leukemia using hedonic techniques. Deryugina (2013)

[4] Agriculture in the west of the United States is predominately irrigated, and western farmers respond in a qualitatively different manner to climate conditions than in regions dominated by non-irrigated (dryland) agriculture. Schlenker et al. (2005) and Schlenker et al. (2006) refine MNS by restricting attention to dryland counties, as well as providing agronomically motivated functional relationships between climate variables. They find the impact of climate change in dryland counties to be between -\$5 and -\$5.3 billion per year (1982 dollars) (Schlenker et al., 2005), and between -\$3.1 and -\$7.2 billion per year using improved weather specifications (Schlenker et al., 2006). Their analysis uses 1982 dollars – throughout the present paper we adjust inputs to 2005 dollars using a CPI adjustment.

[5] The initial application of the Ricardian approach (MNS) was based on land market data from 1978 to 1982. As a result, the results in MNS are most likely immune to the critique presented in this paper. However, the continued application of the myopic Ricardian method to market data from the 2000s and 2010s may no longer be appropriate if markets capitalize expectations about changing future climates, as our empirical results will suggest.

finds that survey respondents update beliefs about climate change in a rational manner. The notion that land markets capitalize expected rents regarding land development, subsidies, and irrigation is recognized in related literature.[6]

Our reading of the literature indicates that expectations over future climate have not been incorporated when estimating the economic impacts of climate change.[7] Our paper extends and complements the new focus on the effects of information and future market forecasts into applied economic analysis by incorporating climate forecasts into the analysis of agricultural land prices. In doing so, we offer a straightforward correction that can be implemented with readily available data and use it to test whether or land markets do indeed reflect future information.

3. Asset prices and information

We develop a simple model of an asset price (P) based on the stream of rents it generates (p) when forecasts of the future state variables are available to the market. By *state*, we refer to potentially time-varying characteristics of an asset that contribute to price formation. In our motivating application, the state variable is climate. Climate has a strong agronomic connection to the agricultural profits that can be produced on a given parcel of land. Similar parcels of land under different climate regimes produce different rents, and thus have different prices.

We treat land as an asset that is rented to firms in order to produce globally traded commodities. A firm can produce any of K products on a parcel of land at any time t. Use k generates gross revenue $v_{kt}(x, \ell, \mathcal{S}_t)$ that depends on inputs x, land characteristics ℓ, and the state variable $\mathcal{S}_t$; the cost of using input vector x is captured by $c_t(x)$. For any use k, firms select inputs to maximize net revenue:

$$r_{kt}(\mathcal{S}; \ell) = \max_x v_{kt}(x, \ell, \mathcal{S}_t) - c_t(x)$$

The subscripted t captures the fact that factors influencing revenue and costs (i.e., prices) may be time varying. Perfect competition among producers implies zero profits for firms on any parcel of land and ensures that firms choose the use of land that maximizes net revenue.[8] The zero profit condition pins down the rental rate, p, of the parcel (suppressing the fixed land characteristics so that $r_{kt}(\mathcal{S}; \ell) = r_{kt}(\mathcal{S})$):

$$\max_k \{r_{1t}(\mathcal{S}_t), \dots, r_{Kt}(\mathcal{S}_t)\} - p_t(\mathcal{S}_t) = 0$$

where we have implicitly assumed that there are zero adjustment costs between uses. While this may be a strong assumption for sectors with high levels of fixed capital, in agriculture many non-land inputs are variable and change year to year (e.g., seed, water, fertilizer), and many capital inputs are mobile (e.g., combines). Kelly et al. (2005) find that adjustment costs in the US Midwest for agricultural in response to climate change are small, well under 1% of the asset value of land. Burke and Emerick (2016) identify little adjustment in agricultural practices to changing climate, either because there are limited options for adjustment or because adjustments costs are too high to be profitably employed. Excluding adjustment costs allows us to collapse dynamic pricing concerns into simple, net present value indices for future climate.[9]

Land is bought and sold in a competitive market, and it is assumed there are no arbitrage opportunities. Thus the price P of the parcel is the present discounted value of future rents and depends on the evolution of the state variable. Given a deterministic future sequence of states $\{\mathcal{S}_0, \mathcal{S}_1, \dots\}$, the asset price is

$$P(\mathcal{S}_0, \mathcal{S}_1, \dots) = \sum_{t=0}^{\infty} p_t(\mathcal{S}_t)\delta^t \tag{1}$$

where $\delta = 1/(1 + r) \in [0, 1)$ is the discount factor, and $r > 0$ is the rate. Thus, the price of land is simply a function of the stream of rents associated with land rental. Equation (1) is a discrete time version of the classic capitalization model of Ricardo (1817) treating land as a fixed factor of production (Nickerson and Zhang, 2014). Rearranging the zero profit condition reveals that the rental rate p is equal to the envelope of land uses.

Much recent work on the climate and agriculture has focused on finding the best functional form to model the relationship between climate and either agricultural production or prices. Three are of particular importance: a quadratic relationship (as in MNS), a binned relationship (Deschênes and Greenstone, 2011), and a piecewise relationship (Schlenker and Roberts, 2009).

[6] In particular, the option to develop land for non-agricultural use greatly influences agricultural land values. Plantinga et al. (2002) estimate that 80% of agricultural land values near urban areas are attributable to development potential. Irrigation, and expectations related to water withdrawals therefrom, impact land prices in the relatively dry region above the Ogallala aquifer (Hornbeck and Keskin, 2014). The role of expectations in the valuation of residential amenities is an active area of research; see, for example Bajari et al. (2012), Bishop and Murphy (2011) and Bishop (2015).

[7] Schlenker et al. (2006) compare coefficients on the hedonic model from 1982 to 1997 to conclude that farmer expectations had not changed over that period. We view this as a weak test and note that that public knowledge of climate change has increased dramatically in recent decades as scientific forecasting of impacts has become more sophisticated and widely disseminated.

[8] In this framework, incumbent landowners are the residual claimants of the economy and the value of their assets could be used to calculate welfare in a general equilibrium analysis.

[9] Several papers examine adjustment costs in the context of residential relocation: Bayer et al. (2016), Bishop and Murphy (2011), Bishop (2015) and Kennan and Walker (2011).

To highlight the role of information, we abstract from these approaches in this section and assume that the rental rate can be represented by a linear approximation of the state variable:

$$p_t(\mathcal{S}_t) \approx a + b\mathcal{S}_t$$

where $b = \partial p/\partial \mathcal{S}$ is the instantaneous change in rental rates due to shifts in the state variable, and a captures the value of fixed determinants of p. In the empirical portion of the paper, we use a nonlinear, piecewise response function, and also report results that use both binned and quadratic specifications in the Appendix. For simplicity, we model p as a constant function up to the state variables.[10] For a deterministic path of future states, the price of the asset at time $t = 0$ is approximated by the present discounted value of the linear approximation of future rents:

$$P(\mathcal{S}_0, \mathcal{S}_1, \dots) \approx \sum_{t=0}^{\infty} (a + b\mathcal{S}_t)\delta^t \tag{2}$$

Note that in the case of a constant state $\mathcal{S}_0$, the price of the asset is simply $P = aD + bD\mathcal{S}_0$ where $D \equiv \sum_{t=0}^{\infty} \delta^t = 1/(1-\delta) = (1+r)/r$.

Now consider two different scenarios, one in which the future states are constant ($\mathcal{S}_t = \mathcal{S}_0 \forall t$) and the other in which the future state evolves ($\mathcal{S}_0, \mathcal{S}_1, \dots$). These scenarios motivate two different models to represent land prices. As we show, both models differ from the standard Ricardian method. It will be convenient to define a simple index, the infinite stream of states associated with each of the two scenarios.[11] Let

$$I \equiv \sum_{t=0}^{\infty} \mathcal{S}_0\delta^t \quad \text{(i.e., the } \textit{No Change} \text{ index)} \tag{3}$$

$$Y \equiv \sum_{t=0}^{\infty} \mathcal{S}_t\delta^t \quad \text{(i.e., the } \textit{Mean Forecast} \text{ index)} \tag{4}$$

Each of these indices captures, in a single variable, the *present value magnitude* of a forecast about the future state. The *No Change* and *Mean Forecast* indices can be used to construct two different asset prices:

$$P(I) \approx aD + bI \quad \text{(the } \textit{No Change} \text{ asset price)} \tag{5}$$

$$P(Y) \approx aD + bY \quad \text{(the } \textit{Mean Forecast} \text{ asset price)} \tag{6}$$

Note the correspondence between the prices associated with each scenario: $P(Y) = P(I) - b \cdot (I - Y)$. The difference $(I - Y)$ captures deviations of expectations about the future from the current state. If markets do capitalize expectations, observed asset price data corresponds to $P(Y)$. In that case, the *No Change* asset price $P(I)$ is unobserved. However, market beliefs about the future state, which we define as the *Mean Forecast* index, are also unobserved. As a result, the dependent variable in Equation (6) is often regressed on the independent variable in Equation (5). We explain how this interchange can bias empirical estimates of b and propose a feasible solution.

3.1. The Ricardian approach in context

When markets capitalize expectations, observed asset price data correspond to $P(Y)$, and $P(I)$ is unobserved. As a result, interchanging prices between Equations (5) and (6) generally misspecifies the theoretical relationship between price and states. In contrast, the standard Ricardian regression ignores the market expectation about the future climate by specifying a model linking land values to observed historical climate[12]:

$$P_i(Y_i) = \alpha + \beta\mathcal{S}_{0i} + u_i \tag{7}$$

The standard Ricardian regression assumes that the state is constant and reports coefficients β that describe the marginal effect of the state on *net present value* of rents. The difference between this coefficient and b (the marginal effect of the state on single period rents) warrants additional caution when predicting the impacts of change in a state: impacts should either be expressed in annual terms or in net present value. This scaling issue can be trivially addressed. We next show how misspecification by replacing Y_i by I_i (or $\mathcal{S}_{0i}$) leads to biased estimates of b.

[10] Relaxing this assumption would require general equilibrium analysis of the changes in crop prices and the prices of inputs, which we consider beyond the scope of this paper.

[11] The only assumption needed to guarantee that this is feasible for $\delta < 1$ is that the states are finite.

[12] The dependent variable in this analysis is the price of land per acre, as in MNS. Many other analyses use the natural logarithm of price per acre. We use a levels specification to match MNS and maintain fidelity to the theoretical model; estimates using log price are similar to those reported in our empirical analysis.

3.2. Standard Ricardian parameters estimates are biased when markets capitalize expectations about future climate change

As the previous section shows, the standard Ricardian approach misspecifies the theoretically correct land value equation when markets capitalize expectations about future climate. This results in an omitted variable bias in empirical implementations. To develop intuition about this bias, we first derive a simple analytic expression for its magnitude and direction when the misspecified equation utilizes the present value magnitude of a forecast (i.e., using I_i instead of Y_i to predict land values). The algebraic simplicity of this bias calculation is muddied when considering the bias generated by estimating the traditional Ricardian regression (where the single state $\mathcal{S}_{0i}$ is substituted for present value index I_i), but the logic is the same.

Suppose that an analyst takes full account of the dynamics of asset markets (and so uses I_i instead of $\mathcal{S}_{0i}$), but implicitly assumes that the market fails to capitalize any expectation about future climate. In that setting, the analyst would incorrectly estimate the marginal impact of a constant state from a regression for land prices that reflect expectations:

$$P_i(Y_i) = \alpha + bI_i + e_i \tag{8}$$

The resulting parameter estimate of b is biased owing to an omitted variable problem. Denote the OLS estimator of b in Equation (8) by $\widetilde{b}$. It follows that:

$$\widetilde{b} \xrightarrow{p} \frac{Cov(I_i, P_i(Y_i))}{V(I_i)} = b\frac{\rho_{IY}\sigma_Y}{\sigma_I} \tag{9}$$

where ρ_{IY} is the correlation between the *No Change* and *Mean Forecast* descriptions of the state, σ_I is the standard deviation of I_i, and σ_Y is the standard deviation of Y_i.[13] Given a sample of data on I_i and Y_i the standard deviation and correlation coefficient σ_I, σ_Y, and ρ_{IY} can all be estimated. Thus the magnitude and sign of the bias in the empirical estimate of b reflects the joint distribution of the forecasts I_i and Y_i. This leads to the following observation:

Result 1. *The incorrect specification of the land value equation that ignores expectations results in a consistent estimate of b ($\widetilde{b} \xrightarrow{p} b$) if and only if $\rho_{IY}\sigma_Y/\sigma_I = 1$ or $b = 0$. In general, the relative bias is equal to $\rho_{IY}\sigma_Y/\sigma_I$.*

This formula for bias deserves a few notes. First, there is one special case where $\rho_{IY}\sigma_Y/\sigma_I = 1$ by necessity. When the *Mean Forecast* description of the state of the world is simply the *No Change* description plus a constant additive term, $\rho_{IY} = 1$ and $\sigma_I = \sigma_Y$, so relative bias is equal to one and b is identified by a regression of $P_i(Y_i)$ on I_i. Second, most climate change forecasts do not predict a 'reversal of fortunes': warmer locales will likely become warmer than cooler locales, implying that $0 < \rho_{IY} < 1$. Thus, if the ratio of standard deviations σ_Y/σ_I is less than one, the bias in the standard Ricardian regression will lead to an understatement of the climate change effects. In particular, if current and predicted climate are not very correlated (as $|\rho_{IY}|$ approaches 0), current climate is a poor proxy for predicted climate and $\widetilde{b}$ is attenuated.[14] At the same time, it is possible that the method overstates damages if $\sigma_Y/\sigma_I >> 1$, as would be the case if cross-sectional variation in predicted climate were much larger than in current climate.

The *Mean Forecast* index is unobserved by the analyst. We therefore make a flexible assumption about the nature of the *Mean Forecast* index in terms of observable data, and derive the bias under this assumption. We utilize this assumption in the empirical exercise, and show that it can be used to predict the degree to which the market is already pricing in expectations about climate change. Suppose that beliefs about the path of future climate (the *Mean Forecast*) can be represented by a mixture between historical climate (the *No Change* index, I_i) and an *Observed Forecast*. This forecast could be extracted from a climate model. Denote the *Observed Forecast* by $F_i \equiv \sum_{t=0}^{\infty} \mathcal{S}_{it}^{\text{Forecast}}\delta^t$. Formally, the assumption that market beliefs are a mixture of historical climate and an observed climate forecast corresponds to the following:

$$Y_i = \omega I_i + (1-\omega)F_i \tag{10}$$

where ω is the weight the market places on the historical, *No Change*, state. Under this assumption, if the analyst proceeds to regress land prices on historical climate alone, the bias in the estimate of b is:

$$\widetilde{b} \xrightarrow{p} b \cdot \left(\omega + (1-\omega)\frac{\rho_{IF}\sigma_F}{\sigma_I}\right) \tag{11}$$

where ρ_{IF} is the correlation between *No Change* and *Observed Forecast* indices, σ_F is the standard deviation of F_i, and σ_I is as before. This reveals that the estimate $\widetilde{b}$ depends not only on the true parameter b and on the statistical relationship between historical climate and the forecast, but it also depends on the weight on the forecast given by the market.

Result 2. *If market beliefs are a mixture of historical climate and an observed forecast, the standard Ricardian approach gives a consistent estimate of b ($\widetilde{b} \xrightarrow{p} b$) if and only if (i) $\omega = 1$ or (ii) $\rho_{IF}\sigma_F/\sigma_I = 1$.*

We can use this result to hypothesize about the direction of this bias in simple linear models. The correlation term is less than or equal to one in absolute value, and is positive in our data; values vary from about 0.5 to 0.99. The ratios of standard deviations

[13] Extending the bias calculation to the multivariate case is less straightforward as it involves the covariances of omitted variables. The intuition is similar, however.

[14] In fact, if $\rho_{IY} = 0$, then $\widetilde{b} = 0$ regardless of b or σ_I, σ_I.

between future climate forecasts and past climate ($\sigma_{S_t}/\sigma_{S_0}$) are generally 0.9–0.95 for growing season mean temperature, and from 0.33 to 0.99 for precipitation. Thus, estimates of b from a linear model that fail to account for expectation will be biased toward zero and the effect underestimated. In the Appendix, we derive an expression for the bias under a piecewise linear function form, and show that the intuition for when the bias occurs is similar. Due to the nonlinearity of the piecewise linear functional form, the implications for the direction of the bias are not as straightforward as in the linear case.

3.3. The economic cost of anticipated future change

The information contained in asset prices can be used to determine both the net present value (NPV) impact of change in the state (e.g., change in the climate) as well as annual impacts to rents. In many ways, the NPV impact of change is the more policy relevant one, for example, in cost-benefit analysis. We therefore focus on the NPV impacts. While it is straightforward to scale between the two impacts given an appropriate measure of b, doing so requires an understanding of the market's discount rate, δ. Furthermore, it may be that society's discount rate differs dramatically from that of the market, a fact which should be accounted for in analysis that compares outcomes and investments over the long term (Weitzman, 1998). In our application, we assume that $\delta = 0.03$ and investigate the robustness of the results to alternative discount rates.

Estimation of the economic costs of anticipated future change proceeds in two steps. The information (forecasts) used in the two steps can be identical or can differ. The first step estimates how asset prices respond to the expected path of future states; this amounts to correctly estimating b. The second step uses a consistent estimate of b and a forecast of future states to estimate the impact of the change predicted by the forecast. Because b captures the price impacts of these changes and prices represent the present value of the states, this approach gives the present value of the changes in the futures states. Given a consistent estimate of b, the impact of any path of state changes can then be predicted.

Predictions of the costs of future changes are made relative to some counterfactual. A relevant counterfactual compares outcomes under some forecast with outcomes had there been no change at all. In the climate change example, this is akin to comparing the prices of land under a change in climate with the prices of the same land if climate was to remain constant. This counterfactual is found simply by estimating the unobserved prices associated with the *No Change* scenario, $P_i(I_i)$. Given data across observations on the current state $\mathcal{S}_{0i}$, the path of future states $\{\mathcal{S}_{ti}\}_{\forall t}$, and prices $P_i(Y_i)$, it is straightforward to generate estimates $\widehat{P}_i(I_i)$. First, following our model, assume the following regression consistently estimates b:

$$P_i(Y_i) = \alpha + bY_i + \varepsilon_i \tag{12}$$

Estimates of the *No Change* price can be constructed with the *No Change* index and $\widehat{b}$:

$$\widehat{P}_i(I_i) = P_i(Y_i) - \widehat{b} \cdot (Y_i - I_i)$$

Once an estimate of the counterfactual price is constructed, the impact of any change in state can be estimated.

A particular case of interest is estimating the impact of change given the market's current beliefs. That is, it would be useful to estimate damages (or benefits) by comparing market expectations to counterfactual prices that reflect no change in state. Only one set of predicted prices needs to be used for this simplified estimate:

$$\text{NPV of impact given current market beliefs} = \sum_i P_i(Y_i) - \widehat{P}_i(I_i) = \sum_i \widehat{b}(Y_i - I_i) \tag{13}$$

The empirical analysis below will illustrate how this NPV can be estimated using readily available data even though Y_i is unobserved.

We make one final comment about price effects in our model. Like all Ricardian models, ours implicitly conducts partial equilibrium analysis. While this assumption is innocuous for local shifts in supply of a globally traded commodity, it may introduce a bias by ignoring general equilibrium price effects as global supply responds. If global productivity effects are small, then the bias introduced by the partial equilibrium approach is also small. Estimates of global changes in agricultural production arising from climate change range from negative effects to positive effects, depending on climate scenario, assumptions about CO_2 fertilization, adaptation, and other parameters. Among three prominent studies (Parry et al., 2004; Calzadilla et al., 2013; Lobell and Gourdji, 2012), we found a range of about a 5% decline in production to about a 1% increase in production, as a result of climate change. If we adopt a price elasticity of demand of −0.4, then these translate into a range of rent effects from +12.5% to −2.5%; these effects arise over the next 50–80 years (depending on the study). Because land markets discount the future, these translate to much smaller price effects. On the other hand, it is possible that global production losses from climate change could be much more significant. In that case, while the concomitant price rise would at least partially offset losses to farmers, consumers would be unambiguously worse off due to lower supply of food and higher prices.

4. Data

The previous section showed that if the land market capitalizes expectations of future climate change, the standard Ricardian regression produces biased estimates. In the context of climate change, these damage estimates are important inputs into policy construction and debate. This and the following sections make three primary empirical contributions. First, we assemble a comprehensive dataset to test whether land markets capitalize readily available climate forecasts; this is the first test of its

kind. Second, we use the results of the empirical analysis to re-estimate the economic impact of climate change on the US agricultural sector; this has important policy implications since current estimates of the damage from climate change contain the bias we have identified. Finally, to close the loop between our theoretical and empirical findings, we estimate the bias in damage estimates that arises from (incorrectly) assuming that markets fail to capitalize predictions of future changes in climate by comparing predictions under both assumptions.

To implement the analysis, we have collected a data set with observations on agricultural land values for 2007, daily average temperature for the growing season and total precipitation (defined over the period the previous 30 years, i.e., 1976–2006), the corresponding future climate predictions for the period 1900–2099 from two different global circulation models, soil quality indicators, as well as other determinants of land values. We also make use of historical agriculture data to further test model implications. We now describe these data and report summary statistics.

4.1. Census of agriculture data

The primary data on agricultural land values are from the 2007 Census of Agriculture. By law, all farms and ranches that produce and sell (or normally would produce and sell) more than $1000 of agricultural products are required to submit a census form. Counties are the finest publicly available geographic unit of observation. The two key variables are the average values of agricultural land and buildings in a county (interpreted in the literature as farmland value, following MNS), and the total acres in farmland in each county. From these we construct average agricultural land values per acre of farmland. This is the dependent variable analyzed in most US applications of the Ricardian approach (Mendelsohn et al., 1994; Schlenker et al., 2005, 2006; Deschênes and Greenstone, 2007; Massetti and Mendelsohn, 2011). We also use the same variables from the 1978–2007 Census of Agriculture to examine whether our empirical estimates of the market belief in climate change varies over time.

4.2. Historical weather data

Weather station data are drawn from the National Climatic Data Center (NCDC) Global Historical Climatology Network-Daily (GHCN-Daily), which is an integrated database of daily climate summaries from land surface stations that are subjected to a common set of quality assurance checks. According to the NCDC, GHCN-Daily contains the most complete collection of U.S. daily climate summaries available. The key variables for the analysis are the daily maximum and minimum temperature as well as the total daily precipitation. We select weather stations that have no missing records in any given year from 1976 to 2006. The station-level data are then aggregated to the county level by taking an inverse-distance weighted average of all the measurements from the selected stations that are located within a fixed 200 km radius of each county's centroid. The weight given to the measurements from a weather station is inversely proportional to the squared distance to the county centroid, so that closer stations are given more weight.

The standard in the recent literature is to relate economic outcomes to climate using functional forms that capture nonlinearities in the effects of climatic variables (Dell et al., 2014). We follow Schlenker and Roberts (2009) and use a two segment piecewise linear regression model in growing season daily average temperature, defined as the average daily temperature over the months of April to September (inclusive). In order to construct historical climate variables we define the climate as the average growing season temperature and total precipitation calculated over the previous 30 years in a given county. For example, for the 2007 Census of Agricultural data, the climate is defined over 1976–2006. We search over a grid of potential breakpoint values and select a breakpoint value that minimizes the Akaike information criteria. This procedure selects a breakpoint at 68.5 ^{o}F; the temperature-land price relationship is allowed to have different slopes above and below this point. This breakpoint is similar to the sample average growing season temperature (69.1 ^{o}F), as we note below. In the Appendix, we also provide results that use the standard quadratic specification from MNS and a binned specification (Deschênes and Greenstone, 2011).

4.3. Climate forecasts

Climate predictions are drawn from the IPCC Fourth Assessment Report (2007).[15] This report synthesizes climate forecasts, and is widely cited and drawn from in lay outlets. Because the climate forecasts we use are the major models used by the IPCC, it is reasonable to assume that these forecasts are also the most readily available to the general public and may thus be considered as information available to the market. Our preferred set of forecasts are obtained from the Hadley Center Coupled Model, version 3 (Hadley 3), which is a coupled atmospheric-ocean general circulation model. It is widely held that this version of the Hadley model contains improvements over previous versions, which improve its ability to generate spatial predictions for a number of reasons. Perhaps most importantly, it improves the ocean resolution and the matching between oceanic and atmospheric sub-models. Essentially, the atmospheric component and the ocean component are run iteratively for one day periods over the length of the entire model simulations (which could be hundreds of years). This and other models of its vintage are now widely used by the scientific community to provide high-resolution spatial predictions of the effects of climate change (e.g. see Thuiller et al. (2005) for an example exploring the spatial effects of climate change on plant diversity in Europe). The

[15] See http://www.ipcc-data.org/sim/gcm_monthly/SRES_AR4/index.html for all data on future climate predictions.

spatial resolution of this model is approximately 300 × 300 km. The changes in temperature and precipitation in non-irrigated US states are roughly in the middle of the ensemble of models used for the IPCC Fourth Assessment Report (Burke and Emerick, 2016). Predictions of climate change from this and other models used in the IPCC Fourth Assessment Report are available for several emission scenarios, corresponding to 'storylines' describing the way the world (population, economies, etc.) may develop over the next 100 years. We focus on the A2 scenario, a "business-as-usual" scenario, which is the proper baseline scenario to consider when evaluating policies to restrict greenhouse gas emissions. As such, predictions from the A2 scenario feature some of the largest predicted increases in global temperature.

Additional climate forecasts are obtained from National Center for Atmospheric Research's Community Climate System Model (CCSM) 3, also a coupled atmospheric-ocean general circulation model included in the IPCC 4th Assessment Report. We focus on the A2 scenario to maintain consistency with the Hadley 3 model. Relative to Hadley 3, CCSM 3 predicts roughly the same level of warming with a greater increase in precipitation (Burke and Emerick, 2016). As with Hadley 3, model predictions from CCSM are widely publicized and are available to the public.

Because the spatial scale of these model predictions differ from one-another, and do not directly align with counties, we use inverse-distance weighted averaging to assign gridded predictions to counties in the same manner as for station-level weather data. All grid points located in a pre-specified radius of a county's centroid are used to assign the climate prediction, with measurements from grid points located further away from the centroid receiving less weight. A radius of 200 km ensures that every county gets a prediction. From these daily grid point level data we construct the same measures of average temperature for the growing season and total precipitation for every county and year.[16] Climate predictions from both models are largely consistent across counties in our sample.[17]

In order to correct for inherent aggregate model bias that takes effect at the county level, we use model predictions of historical climate and actual historical climate to create corrected climate predictions following Auffhammer et al. (2013). In particular, we utilize 'Climate of the 20th century' runs of the Hadley 3 and CCSM 3 models and average together the preceding 30 years for each climate variable and county i ($\overline{S}_{i,t}$). We correct using the corresponding 30-year average for historical weather ($S_{0i,t}$) as follows:

$$S_{i,t} = S_{i,t}^{predicted} + \left(\overline{S}_{i,t} - S_{0i,t}\right)$$

Because the 'Climate of the 20th century' runs only cover the period 1900–1999, for data years 2002 and 2007 we correct using the average of data from 1969 to 1999.

4.4. Public opinion data on climate change

To provide an additional test of our model, we utilize high resolution (county-level) estimates of climate change perceptions from Howe et al. (2015). This dataset contains estimates of climate change perceptions constructed using multiple climate surveys and multilevel regression and poststratification (MRP) techniques. The underlying survey data are taken from twelve nationally representative surveys conducted by the Yale Project on Climate Change Communication and George Mason Center for Climate Change Communication between 2008 and 2013. Because these perception data are model estimates based on survey data in combination with demographic and geographic predictors, Howe et al. (2015) perform both internal cross-validation and external validation with independent, sub-national surveys to verify the strength of their approach. MRP techniques in combination with validation have been found to more accurately predict public opinion at disaggregated geographies than other methods (Warshaw and Rodden, 2012).

4.5. Other predictors of agricultural land value

We also include soil quality variables in this analysis, specifically measures of susceptibility to floods, soil erosion (K-Factor), slope length, sand content, irrigation, and permeability. The underlying data come from the National Resource Inventory (NRI). The NRI is a large-scale survey of soil samples and land characteristics from roughly 800,000 sites in the United States. These variables are calculated as weighted averages across sites used for agriculture, where the weight is the amount of land the sample represents in the county. See Deschênes and Greenstone (2007) for more details. Finally, we include controls in per capita income and population density.

4.6. Sample construction and summary statistics

Our sample consists of all counties located east of the 100th meridian with valid measurement on farmland values in the 2007 Census of Agriculture. We restrict the analysis to counties located east of the 100th meridian following Schlenker et al. (2006)

[16] The inverse distance weighting approach to assign future climate to counties created a few anomalous assignments. These counties, primarily in Michigan, are excluded from this analysis. Consolidated cities in Virginia were also excluded. In total, 39 counties are excluded; full details are in Appendix I.

[17] The correlation coefficients between the Hadley 3 A2 and CCSM 3 A2 model predictions for precipitation and growing season mean temperature range from 0.92 to 0.99.

since those counties rely primarily on rainfall as opposed to irrigation like the counties in the American West. Because climate likely has a different effect on urban land prices, and urban land prices can affect agricultural land prices through the potential for development (Plantinga et al., 2002), we follow Schlenker et al. (2005) and exclude counties with a density of more 400 people per square mile or a population greater than 200,000 at any point in our sample. The final sample consists of 2112 counties and the sample average value of land and buildings per acre is \$2834 (in 2005 dollars). The average growing season temperature for the 2112 counties over 1976–2006 is 69.1 ^{o}F and ranges from 55.6 ^{o}F to 82.9 ^{o}F.

5. Empirical application

We now turn to implementing the theoretical asset pricing model to determine whether expectations regarding climate change predict current agricultural land prices in the United States. Cross-sectional hedonic estimation methods potentially suffer from many identification pitfalls, and addressing all of these satisfactorily is beyond the scope of this paper. Instead, we focus on understanding the role expectations of climate change may already be playing in land markets through cross-sectional and panel hedonic regression models.

5.1. Empirical specification

Ideally, we could directly implement an empirical version of Equation (12) in the theoretical model:

$$P_{is} = \alpha + Y_{is}'b + X_{is}'\xi + \gamma_s + \varepsilon_{is} \tag{14}$$

where P_{is} is the observed price per acre of land in county i in state s and Y_{is} is the index of beliefs about future climate change used by the market. Other county and land characteristics are included in X_{is}. This includes both variables that are potentially exogenous with respect to our measures of climate (such as soil salinity and slope), and variables that may be correlated with land values (such as development pressure and other demand variables). Our preferred specification includes state fixed effects (γ_s) to capture state-specific unobserved factors that predict land values (and may be correlated with climate) such as agricultural policy, taxes, uncertainty, etc. Since there may be a limited extent of climatic variation within some states (both historically and in terms of future climate predictions from GCMs), we also report estimates from models that exclude state fixed effects. In general, both sets of estimates are qualitatively similar.

Recall that Y represents an index of beliefs about the future climate: $Y \equiv \sum_{t=0}^{\infty} \mathcal{S}_t\delta^t$. The central issue in implementing regression model in Equation (14) is that while a variety of climate forecasts are observable by landowners and by the econometrician, actual market beliefs (Y) are not observed. It follows that implementing such regression models requires assuming a model for Y. We develop an approach that incorporates both historical climate data and climate forecasts. The two climate models compete to explain observed land prices, and provide an empirical test for whether land prices are formed on the basis of historical or future climate.

5.2. Testing whether land markets capitalize expectations

Though the analyst does not directly observe Y, data are readily available on many climate forecasts as well as on current and historical climate. These climate forecasts have been developed in part for the IPCC's Assessment Reports, and have been frequently reported by various media outlets and discussed extensively by policy makers and scientists.[18] While individuals may not be directly aware of all this information, it is reasonable to expect a forward-looking market to have capitalized this information into the average county prices we observe. Thus, we can use these data to develop plausible estimates of climate change beliefs, although alternative data and information sets surely are used by rational market agents.

Instead of taking a firm stance on which forecast best represents market beliefs, we utilize a flexible parametric model that permits linear mixing of different climate scenarios. The model estimates a weight parameter that determines the relative importance of a particular climate model to best match observed prices. This parameter can also be interpreted as the degree to which the market 'believes' that climate forecast. To maintain tractability, we select two climate change scenarios: a no-change scenario (S_{0i} represented by historical climate variables that are used in the standard application of the Ricardian method), and an observed forecast scenario (S_{it}, represented by the data from either the Hadley 3 or CCSM 3 Scenario A2 models). We assume that market beliefs are a weighted average of the no-change and observed forecast scenarios.[19] Specifically, suppose we consider data dated from 2007 to 2099 and let $\hat{Y}_i$ be the constructed *Mean Forecast* for county i:

$$\begin{aligned}\widehat{Y}_i(\omega) &= \sum_{t=2007}^{2099} \omega S_{0i}\delta^{t-2007} + \sum_{t=2007}^{2099} (1-\omega)\, S_{it}\delta^{t-2007} \\ &= \omega I_i + (1-\omega)F_i \end{aligned} \tag{15}$$

[18] In fact, the IPCC has ensured that the results of thousands of climate change simulations performed by seventeen scientific collaborations are available in common format to the general public.

[19] We focus on two scenarios, but adding additional scenarios is straightforward.

where $F_i = \sum_{t=2007}^{2099} S_{it}\delta^{t-2007}$ corresponds to the *Observed Forecast* index in Section 3.1. The data specify the *Mean Forecast* index up to a scalar parameter ω that can be estimated jointly with the other parameters of the model (but maintaining an assumed value of δ). This structural parameter defines the weighting the market places on each of the two climate change scenarios.[20]

An advantage of this parameterization is that it permits testing whether or not land markets are capitalizing expectations. Because the constructed market beliefs above include historical (no change) climate as one of the climate scenarios, the parameter $\omega \in [0, 1]$ can be interpreted as the weight the market places on the possibility that climate will not change. If $\omega = 1$, then the market places no weight on expectations about the future climate. This is implicitly the assumption made in current applications of the standard Ricardian method. Alternatively, if $\omega < 1$, then the market places some weight on the *Observed Forecast* F_i, and beliefs about climate change are being capitalized in the land market.

The feasible version of Equation (14) is given by:

$$P_{is} = \alpha + \widehat{Y}'_{is}(\omega)b + X'_{is}\xi + \gamma_s + \varepsilon_{is} \tag{16}$$

where $\{\alpha, b, \omega, \xi, \gamma\}$ are all parameters to be estimated. Since the vector of parameters b and the scalar parameter ω enter multiplicatively, we estimate Equation (16) using non-linear least squares (NLLS) to jointly estimate b and ω. Since ω enters Equation (16) linearly, calculation of the marginal effects is not complicated by non-linearities in ω. However, the interpretation of the marginal effects needs qualification: b captures the effect of marginal changes in the constructed market beliefs $\hat{Y}(\omega)$, not of historical climate. Finally, since we interpret ω as a weight, we expect it to lie on the unit interval. Most specifications yield results such that $\widehat{\omega} \in [0, 1]$, or statistically indistinguishable from the boundaries. In the few cases this does not occur, we normalize ω to lie in the unit interval.[21]

6. Empirical results and discussion

We apply the forward-looking Ricardian method by estimating Equation (16); we then present the parameter estimates and predicted climate change damages. We have three specific objectives. First, we confirm that the indices formed from climate forecasts are relevant predictors of land values. We report the OLS coefficient estimates from Ricardian regressions that include both historical climate indices (based on the 1976–2006 averages in seasonal weather) and forecast climate indices (based on the Hadley and CCSM data for 2007–2099). This analysis provides a simple test of whether forecast climate indices are relevant predictors of current land values conditional on the historical climate indices and serves as motivation for the ensuing NLLS estimation procedure.

In the second part of the analysis, we test whether land markets capitalize expectations about future climate by estimating the parameter ω in Equation (16) and performing the required statistical test. We also estimate and report the theoretically correct climate-price gradient parameters b. This section illustrates that the proposed forward-looking Ricardian method is empirically relevant and simple to implement with readily available data. Furthermore, we show that this critique is useful across a variety of model specifications.

Third, we use the empirical estimates of b and ω to derive the predicted damage of climate change on U.S. agriculture assuming that climate evolves in a manner consistent with market beliefs. We compare the market's expected damage estimates obtained from the theoretically correct forward-looking Ricardian method and the 'myopic' versions based on Equation (8). The results are substantially different, and indicate that failing to control for market beliefs causes the analyst to misstate the impacts of climate change.

We perform several additional tests that validate the importance of accounting for market beliefs. We exploit spatial heterogeneity in perceptions of the likelihood of climate change and show that variation in county-level climate change perceptions impacts the relationship between climate and the price of agricultural land in a reasonable manner. We also confirm that our results are not sensitive to the choice of discount rate. Finally, we pool data on land values, climate, and climate expectations over 1978–2007 to estimate how the climate change belief parameter (ω) has evolved through time.

At the same time, we acknowledge that there are a large number of factors that affect land values, and as such, the cross-sectional regression estimates we report here may still reflect omitted variable bias.[22] The approach we propose identifies and addresses one important source of bias, and suggests that commonly used approaches for addressing omitted variables bias (such as including fixed effects) may be insufficient in the case of outcomes of forward-looking markets. Since our empirical model does not control for unobserved land value determinants that may be correlated with climate, we do not claim that the empirical estimates reported in the paper correspond to 'causal' estimates of the climate-price gradients. Nevertheless, to minimize concern about spatially correlated omitted variables, our preferred specifications include state fixed effects (Kuminoff et al., 2010).

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20 We model climate as a piecewise linear function in temperature. This means that climate is piecewise vector in temperature: $\begin{pmatrix} \omega I_i + (1-\omega)F_i \\ \omega I_i 1_{[I_i > \overline{T}]} + (1-\omega)F_i 1_{[F_i > \overline{T}]} \end{pmatrix}$ where $\overline{T}$ is a temperature breakpoint. Precipitation is binned.

21 This occurs only during exploring the robustness of $\delta = 0.03$. In this case: $\omega = g(\widetilde{\omega}) = \frac{1}{1+\exp(\widetilde{\omega})}$ where $\widetilde{\omega}$ can take any value on the real number line.

22 Recent research demonstrates that cross-sectional hedonic regressions may produce unreliable estimates in a variety of settings (Black, 1999; Chay and Greenstone, 2005; Deschênes and Greenstone, 2007.

Table 1
Estimated marginal effects from OLS coefficients from ricardian regressions including historical climate and predicted future climate indices, 2007 cross-section.

	Historical Climate Indices Only		Historical and Expected Climate Indices			
	(1)	(2)	Historical (3a)	CCSM 3 (3b)	Historical (4a)	Hadley 3 (4b)
Growing Season Average Temperature Index:						
Temperature < 68.5 °F	−4.88*	−2.10	10.07	−8.07	6.27	−5.04
	(2.09)	(2.37)	(5.49)	(4.20)	(5.24)	(4.05)
Temperature ≥ 68.5 °F	−12.94***	−10.55**	3.15	−12.93**	0.06	−10.10*
	(2.52)	(3.01)	(5.20)	(4.81)	(5.16)	(5.05)
Annual Precipitation Index:						
Annual Precipitation Less Than 24 in	−21.63*	−27.23***	−20.57**	−32.81*	−22.18***	−32.83*
	(10.01)	(4.84)	(6.03)	(14.13)	(5.35)	(15.18)
Annual Precipitation Between 24 and 36 in	−0.25	−7.84	−9.21**	−3.54	−8.73*	−2.79
	(6.51)	(4.54)	(3.15)	(7.40)	(3.44)	(8.03)
Annual Precipitation Between 36 and 43 in	–	–	–	–	–	–
	–	–	–	–	–	–
Annual Precipitation Between 43 and 51 in	5.44	−4.48	−1.64	−15.73	−1.38	−26.38*
	(6.27)	(3.64)	(3.17)	(8.06)	(3.11)	(9.98)
Annual Precipitation Greater Than 51 in	17.80	10.91	13.04*	0.57	11.83*	0.41
	(8.88)	(5.50)	(5.02)	(7.95)	(4.94)	(9.10)
F-statistic on 6 indices	7.62	8.45	6.38	3.20	6.50	3.32
[p-value]	[0.000]	[0.000]	[0.000]	[0.013]	[0.000]	[0.011]
State Fixed Effects	No	Yes	Yes		Yes	
Observations	2112	2112	2112		2112	

Notes: Dollar figures in 2005 constant dollars. All entries are from farmland value per acre piecewise linear regressions on the historical and predicted future climate indices. Standard errors are clustered on state. Asterisks denote p-value <0.05 (*), <0.01 (**), <0.001 (***). See the text for more details on the other control variables included in the regressions.

6.1. Estimates for US agricultural land east of 100th meridian

Our primary specification utilizes cross-sectional data from the 2007 Agricultural Census for the agricultural counties located east of the 100th meridian. By 2007, the possibility of climate change was plausibly in the information set of farmers and market participants, particularly given the broad media attention given to the topic throughout the early 2000s. Various polls suggest that the American public is concerned about the possibility of climate change (for example, Howe et al. (2015) and Leiserowitz (2007)). As such it is reasonable to assume that observed land values reflect expectations about the future climatic conditions associated with each county.

Table 1 begins the analysis by reporting OLS coefficients from Ricardian regressions that include six historical climate indices. We first model the effect of temperature through a piecewise linear regression and include separate effects of growing season average temperature around the breakpoint of 68.5 F. For annual precipitation we construct five bins roughly corresponding to quintiles of the 1976–2006 distribution: less than 24 inches, between 24–36, 36–43, and 43–51 inches, and more than 51 inches annual precipitation. The 36–43 inches bin serves as the omitted category.

The corresponding estimated coefficients are reported in columns (1) and (2) of Table 1. The coefficient estimates from columns (3a)-(4b) are from regressions that include both the six historical climate indices and six forecast climate indices from the Hadley 3 or CCSM 3 Scenario A2 data. Since both the historical and forecast climate indices are scaled up by the proportionality factor D associated with the 3% discount rate, the coefficient estimates can be interpreted as the PDV of a one degree increase in average growing season temperature, with a potentially different slope above or below the breakpoint over the period 2007–2099 on 2007 land values. The coefficients on the annual precipitation bins measure the PDV of changing precipitation from the reference category (36–43 inches) to any of the other four categories. Finally, the standard errors associated with the estimates in Table 1 (and all other tables) are clustered at the state level in order to allow for spatial correlation of the regression errors within states.[23]

The estimated coefficients in columns (1) and (2) are generally similar and indicate that increases in average growing season temperatures beyond 68.5 F reduce land values. Low rainfall areas (e.g., less than 24 inches) also have lower farmland values. Because climate is measured in PDV units, coefficients must be scaled appropriately (by the proportionality factor, $D = 32.1$ based on $r = 0.03$). For example, the coefficients in column (2) reveals for example that a sudden one degree increase in average growing season temperature above 68.5 F sustained between 2007 and 2099 is associated with a $-10.55 \times D = \$339.04$ per acre

[23] There are 37 states in the sample and so concerns about cluster-robust inference with a small number of groups are likely secondary here.

Table 2
Estimated coefficients from forward-looking ricardian regressions, 2007 cross-section.

	Beliefs based on CCSM 3 A2				Beliefs based on Hadley 3 A2			
	(1a)	(1b)	(1c)	(1d)	(2a)	(2b)	(2c)	(2d)
Parameter								
ω	0.42+	(0.22)	0.47***	(0.12)	0.39+	(0.23)	0.42**	(0.12)
Growing Season Average Temperature Index:								
Temperature < 68.5 °F	−1.26	(2.46)	1.05	(2.20)	−1.50	(2.30)	1.26	(2.24)
Temperature ≥ 68.5 °F	−12.621***	(2.59)	−10.28***	(2.88)	−12.84***	(2.54)	−10.07***	(2.79)
Annual Precipitation Index:								
Annual Precipitation Less Than 24 in	−35.81*	(14.13)	−40.54***	(8.35)	−36.23*	(14.07)	−40.91***	(9.91)
Annual Precipitation Between 24 and 36 in	0.78	(10.35)	−8.79	(7.68)	8.24	(13.00)	−6.11	(8.58)
Annual Precipitation Between 36 and 43 in	–	–	–	–	–	–	–	–
Annual Precipitation Between 43 and 51 in	4.10	(12.06)	−11.55+	(5.80)	6.41	(16.09)	−13.40+	(6.84)
Annual Precipitation Greater Than 51 in	15.31	(11.92)	16.17+	(9.26)	19.01	(13.78)	18.01+	(9.82)
F-statistic on 6 indices	8.44		10.62		8.80		6.85	
[p-value]	[0.000]		[0.000]		[0.000]		[0.000]	
State Fixed Effects	No		Yes		No		Yes	

Notes: Dollar figures in 2005 constant dollars. All entries are from farmland value per acre piecewise linear regressions on the constructed future climate expectation index (Equation 15). Standard errors are clustered on state. Asterisks denote p-value < 0.10 (+), <0.05 (*), <0.01 (**), <0.001 (***). See the text for more details on the other control variables included in the regressions.

decrease in land values.[24]

The regression model underlying the estimates in columns (3a) - (4b) incorporates both forecast climate indices and historical climate indices. The estimated coefficients associated with each seasonal climate variable are reported in two sets of columns, corresponding to the same regression equation (i.e., (3a) and (3b) are from the same regression equation). Columns (3a) and (4a) show the coefficients associated with the historical climate indices, while columns (3b) and (4b) report the coefficients of the expected climate indices based on the CCSM forecast and the Hadley forecast. The specifications in columns (2), (3a)-(3b), and (4a)-(4b) include state fixed effects to control for unobserved time-invariant predictors of farmland values that may vary at the state level. We note that inspecting columns (1) and (2) (for historical indices only) and (3b) and (4b) (which include climate forecasts), the effects of temperature on land value are highly nonlinear. This underscores the spatially-heterogeneous effects of climate change and drives home the importance of the forward-looking approach.

The F-statistics reported in the bottom of Table 1 test the joint significance of each of the relevant six climate indices in the regressions and indicate that forecast climate indices are important predictors of current land values. In each specification, each set of climate indices (historical and forecast) are jointly significant with p-values less than 0.02. For example, when the forecast climate indices are constructed using the CCSM data (column 3b), the F-statistic is 3.20, while the corresponding F-statistic for the Hadley forecast indices (column 4b) is 3.32. By comparison, the F-statistics associated with the historical climate indices are 6.38 and 6.50. The importance of the forecast climate indices as predictors of land values is also evident since the estimated negative effect of high temperatures on land value is larger (and statistically significant) for the forecast climate indices and not for historical climate indices (see columns (3b) and (4b). We now turn to a more structured analysis of whether land markets capitalize expectations about future climate by estimating the parameters of the forward-looking Ricardian model.

Table 2 reports the NLLS regression parameters estimates from Equation (16) along with the estimated standard errors. Columns (1a) - (1d) correspond to the estimates from the model with market beliefs formed using the CCSM forecast, and columns (2a) - (2d) correspond to the case with market beliefs formed using the Hadley forecast. In each case, the (a) and (c) columns report the parameter estimate, and the (b) and (d) columns report the estimated standard error. The (a) and (b) columns are from models that exclude state fixed effects, and the (c) and (d) columns are from models that include them. In each regression, there are 6 climate parameters, corresponding to the average growing season temperature terms (below/above 68.5 ^{o}F) and the annual precipitation bins variables.

The first row in Table 2 reports the estimate of the parameter ω, the weight assigned by the market to the *No Change* (as opposed to the *Observed Forecast*) scenario. Recall that ω can be interpreted as the market's belief that climate change will not occur; $1-\omega$ then represents the market belief that climate change will occur (as represented by either the Hadley or CCSM models). Across all specifications the estimated parameter ranges from 0.39 to 0.47 and the hypothesis that $\omega = 1$ is rejected with a p-value less 0.05 in all models. In the prefered specification that include state fixed effects the estimate of ω is slightly larger and is also statistically different from 0 at the 5% level. Adding to the evidence presented in Table 2, it is clear that expectations about the future climate appear to already be priced in the agricultural land markets.

The next rows of Table 2 report the estimated effects of the individual components of $\widehat{Y}_i(\omega)$ on land values. The F-statistics reported in the bottom of Table 2 indicate the land market capitalizes the information about future climate that is contained in the constructed forecast indices. These test the joint significance of the 6 variables in $\widehat{Y}_i(\omega)$ that are included in the NLLS

[24] The model specification is such that a one unit increase in Y_i is equivalent to $1/D = 0.031$ sustained increase from 2007 to 2099 (with $r = 0.03$).

Table 3
Estimated impacts of climate change, main estimation sample, discounted to 2007, billions of 2005 dollars.

	Effect of climate change accounting for beliefs		
	Composite index based on CCSM3 A2 ($Y_i(\omega)$) (1)	Composite index based on Hadley3 A2 ($Y_i(\omega)$) (2)	No Change index (I_i) (3)
Present Value of Climate Change Impacts			
CCSM 3	−215.4*	−192.3*	−506.9**
	(85.4)	(76.0)	(174.9)
Hadley 3	−226.6*	−202.2*	−453.0**
	(92.7)	(82.7)	(155.8)
Annualized Value of Climate Change Impacts			
CCSM 3	−6.70*	−5.98*	−15.77**
	(2.66)	(2.37)	(5.44)
Hadley 3	−7.05*	−6.29*	−14.10**
	(2.89)	(2.57)	(4.85)
State Fixed Effects	**Yes**	**Yes**	**Yes**

Notes: The estimated impacts of climate change are derived from the state fixed effects regressions summarized in Table 2, with corresponding column numbers, i.e., columns (1) and (2) in Table 3 correspond to columns (1c) and (2c) in Table 2. The future climate expectation indices underlying the regressions are constructed with a discount rate of 3% and so implicitly the reported impacts are discounted assuming a 3% discount rate. Standard errors in parentheses are linear combination of regression standard errors clustered by state. Asterisks denote p-value < 0.05 (*), <0.01 (**), <0.001 (***).
N counties = 2112.

regressions. In the case of beliefs based on the CCSM forecast (1a) and (1c), the F-statistics are 8.44 and 10.62, while for beliefs based on the Hadley forecast (2a) and (2c), the F-statistics are 8.80 and 6.85. In all cases the p-values associated with these tests are 0.001 or less.

The estimated coefficients again indicate that expectations about future climate change predict current farmland prices. Like in Table 1, the strongest negative predictors of land values are average growing season temperature above 68.5 °F and annual precipitation less than 24 inches. Further, the results are robust to both specifications of the forecast climate indices. In particular, comparison of the coefficients in (1a) and (2a), and (1c) and (2c) reveals estimated effects that are generally of same sign and similar magnitude across the two specifications of climate change beliefs. It is notable that the inclusion of the state fixed effects does not generally alter the statistical significance of the estimated coefficients: all of the statistically significant coefficients in columns (1a) and (2a) remain significant in columns (1c) and (2c). Given this, we now focus on the specification with state fixed effects as it appears well identified in the data and provides better control against omitted variables bias.

Table 3 reports the total present value of the climate change impacts as well as the corresponding annualized impacts. The annualized impacts are calculated by scaling the total present value impacts by the proportionality factor implied by the discount rate of 3%. The annualized impact is interpreted as the average yearly impact of climate change over the period 2007–2099, while the total present value is simply the sum of discounted impacts from 2007 to 2099. We report estimates corresponding to three different models of beliefs about future climate change: beliefs given by the weighted sum of the *No change* index I_i and the CCSM3 *Observed forecast* index F_i (with weight corresponding to the empirical estimate of ω in column (1c) of Table 2), beliefs given by the weighted sum of the *No change* index I_i and the Hadley *Observed forecast* index F_i (with weight corresponding to the empirical estimate of ω column (2c) of Table 2), and beliefs based only on the *No change* index I_i. This final set of beliefs corresponds to the approach taken in previous applications of the Ricardian method, which imply the restriction $\omega = 1$.

The present value of the change in farmland values due to climate change across all counties in columns (1) and (2) of Table 3 is given by applying Equations (13) and (15) to a specific model for belief formation, and the related empirical estimate of ω, denoted by $\widehat{Y}_i(\widehat{\omega})$:

$$\sum_i (\widehat{Y}_i(\widehat{\omega}) - I_i)'\widehat{b} = (1-\widehat{\omega})\sum_i (F_i^{\text{Had3A2 or CCSM3A2}} - I_i)'\widehat{b}_{\text{Forward-looking}}$$

This measure of damages corresponds to the total impact of climate change if climate evolves as the market anticipates (i.e. following the linear mixture of historical climate and forecast climate). We calculate the effects of climate change under the myopic, *No Change* Ricardian model as

$$\sum_i (F_i^{\text{Had3A2 or CCSM3A2}} - I_i)'\widehat{b}_{\text{Myopic}}$$

This myopic value suffers from two sources of bias: (i) the estimated values of $\widehat{b}$ may be biased, and (ii) it is implicitly assumed that $\omega = 0$.[25]

[25] Alternative analysis could predict the impact of climate change if climate evolves precisely according to the climate forecast, F_i, rather than according to mean market beliefs, $Y_i(\omega)$. This would remove the second source of bias in the myopic results. Such estimates can easily be calculated by multiplying the results presented in Table 4 by an adjustment factor of $1/(1-\omega)$. This adjustment factor is greater than one and would increase the absolute magnitude of estimated damages. For example, if ω were to equal 0, the predicted climate change damages would be −406.6 and −391.5 (CCSM3 composite index) and −363.0 and −349.3 (Hadley3 composite index).

Table 4
Impact of geographical heterogeneity in climate change perception on estimated market belief parameters (ω), 2007 cross-section.

	Beliefs based on CCSM 3 A2			Beliefs based on Hadley 3 A2		
	(1)	(2)	(3)	(4)	(5)	(6)
Share believing climate change is happening (SCCH)	–	16.14*	41.73**	–	15.99*	37.70*
		(7.66)	(14.90)		(7.83)	(14.88)
Market belief parameter (ω)	0.47***	0.47***	–	0.42**	0.42**	–
	(0.12)	(0.12)		(0.12)	(0.12)	
Predicted ω as a function of SCCH						
low SCCH (SCCH = 45)	–	–	0.81***	–	–	0.77***
			(0.12)			(0.14)
mean SCCH (SCCH = 57.7)	–	–	0.53***	–	–	0.49***
			(0.13)			(0.13)
highest SCCH (SCCH = 76)	–	–	0.14	–	–	0.14
			(0.14)			(0.14)
F-statistic on 6 indices	10.62	12.30	12.60	6.85	7.51	7.86
[p-value]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
State Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Dollar figures in 2005 constant dollars. All entries are from farmland value per acre piecewise linear regressions on the constructed future climate expectation index (not reported) interacted with the market belief parameter ω. Specifications in columns (3) and (6) allow the market belief parameter to depend on county-specific perceived likelihood of climate change. Standard errors are clustered on state. The standard errors do not account for the sampling variability introduced by including the SCCH variable (estimated share of population believing in climate change). Asterisks denote p-value < 0.05 (*), <0.01 (**), <0.001 (***). See the text for more details on the other control variables included in the regressions.

Table 3 indicates that if beliefs are defined as a mixture of the CCSM data and historical climate and the estimated model describes how climate indeed evolves, the total present value damage of climate change is \$215.4 billion over the next century, annualized to \$6.7 billion (column (1), rows 1 and 3). On the other hand, if beliefs are defined as a mixture of CCSM data and historical climate and the future climate path instead follows a mixture of historical climate and the Hadley forecast, the predicted total present value damage of climate change is slightly larger at \$226.6 billion. These estimates, like all others reported in Table 4, are statistically significant at the conventional level. The other predicted impacts in columns (1) and (2) correspond to the case where beliefs are modeled on one climate model, but the realized future climate path evolves according to the other. These estimates are qualitatively similar to the others.

By comparison, estimates of the present value of damages up to 2099 from the application of standard Ricardian approach (the 'No change' index in column 3) range from \$453 to \$507 billion. Estimates of the impact of climate change that account for the fact that the land market capitalizes expectations about future climate are smaller in magnitude than standard Ricardian estimates by 50%–62%, depending on the specifics of the model. Notably, all estimates in Table 3 are negative (indicating net losses from climate change) and are relatively large (the entire value of US agricultural farmland, buildings, and holdings in 2007 was \$1.74 trillion, while total production and payments to the agricultural sector was about \$297 billion in 2007).[26] The bias demonstrated in the theoretical section is economically important: In dollar terms, the bias in the myopic Ricardian model (i.e. comparing column (3) to (2) and (1)) is large and corresponds to about 18% of total US agricultural farmland, buildings, and holdings in 2007.

While Table 3 reports estimates of the climate change impacts from the baseline specification in six climate variables, we also explore the robustness of these results to alternative functional forms. Appendix Table 2 report the NLLS coefficients estimates (corresponding to Table 2) and the predicted climate change impacts (corresponding to Table 3) when the specification of the forward-looking Ricardian regression is based on the original MNS specification (linear and quadratic terms in average season temperature and precipitation, for a total to sixteen climate variables). The estimated climate change impacts based on the quadratic climate indices specification are larger than the ones reported in Table 3, although the differences are small relative to the difference in the standard errors. The estimated total present value of the climate change impacts range from predicted losses of \$396 to \$777 billion. More importantly, the estimates of the market's belief parameter ω from the model where the climate variables are represented by quadratic terms range from 0.31 to 0.51, largely consistent with the estimates of ω reported in Table 2. Appendix Table 3 similarly reports NLLS coefficient estimates and predicted climate change impacts when the specification of the forward-looking Ricardian regression is based of these flexible bins in long-run average temperature and total precipitation. Specifically, we define 10 temperature bins as follows: one for the number of days with daily mean temperature less than 10 °F, one for the number of days daily mean temperature greater than 90 °F, and the eight 10 °F wide bins in between. For each county we then average these bins over the 1976–2006 period, which produces the long-run average number of days per county-year where daily average temperature falls in each of the 10 categories. The annual precipitation variables are modeled using the same bins definition described in section 6.1. While the estimated climate change impacts based

[26] These values are from the 2007 US Census of Agriculture.

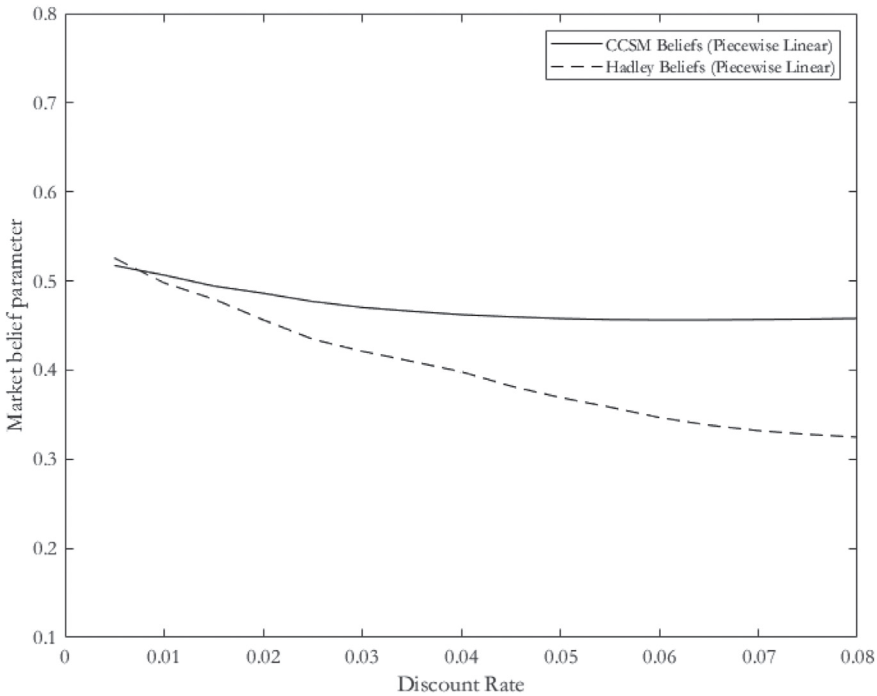

Fig. 1. Estimated market belief parameters in climate not changing (ω) as a function of the discount rate.

on the binned climate indices specifications are smaller than the ones reported in Table 3 and Appendix Table 2, the magnitude of ω is similar.[27]

6.2. Varying the discount rate

The empirical implementation of the forward-looking Ricardian model requires an assumption about the discount rate. In the preceding analysis, we assumed a discount rate of 3% to reflect the long run nature of rural land investments. For policy analysis relating to climate change or other multi-generational phenomena, economic arguments justify using discount rates that more closely equate distant future and near term time horizons (Weitzman, 1998). In this case 3% may be too large or small, so we estimate damages over a range of discount values from [0.5%, 6.5%]. This covers a wide range of time horizons.[28]

Fig. 1 shows the estimated ω and climate change impacts associated with a wide range of discount rates. As in the prior analysis, these results are based on beliefs constructed from the Hadley and CCSM data and we use the same piecewise linear regression in average growing season temperature that underlies Tables 2 and 3 The estimates in Fig. 1 are obtained from estimating versions of Equation (16) that are constructed using the different assumptions on the discount rate (in order to form $\widehat{Y}(\omega)$) and that include state fixed effects and all the other control variables. Overall, we find that the estimated market belief parameters are similar for the range of discount rates we consider. For the beliefs constructed using the Hadley data the estimates of ω range from 0.34 to 0.53, while for the beliefs constructed using the CCSM data, the estimates of ω range from 0.46 to 0.52. Thus it is evident that the estimates of ω reported in Table 3 are not strongly influenced by the choice made on the discount rate. Fig. 2 graphically reports the estimated climate change impacts associated with the various discount rates. These are obtained from the same regressions underlying Fig. 1. The entries are in billions of 2005 dollars. Several noticeable patterns emerge from Fig. 2. As expected, it is evident that predicted damages are larger when the discount rate is smaller. For example, the damages associated with a discount rate of 1% are around negative $250 billion for both sets of constructed beliefs. A discount rate of 3% returns the same damage estimates as those reported in Table 3 (-$202.2 for Hadley and -$215.4 for CCSM). For larger discount rates, the gap between the Hadley-based and CCSM-based damages grows: for example when the discount rate is 6.5%, the CCSM damage is 34% larger than the Hadley-based damage.

[27] A caveat of this specification is that it imposes stronger information demands on the land market buyers who need to pay attention to variability in the numbers of days in each bin, not just the average growing season temperature as in the piecewise linear model.

[28] For example, a constant revenue stream reaches 95% of its discounted value after 98 years with a discount rate of 3%, while this takes 297 years with a discount rate of 1% and 58 years with a discount rate of 5%.

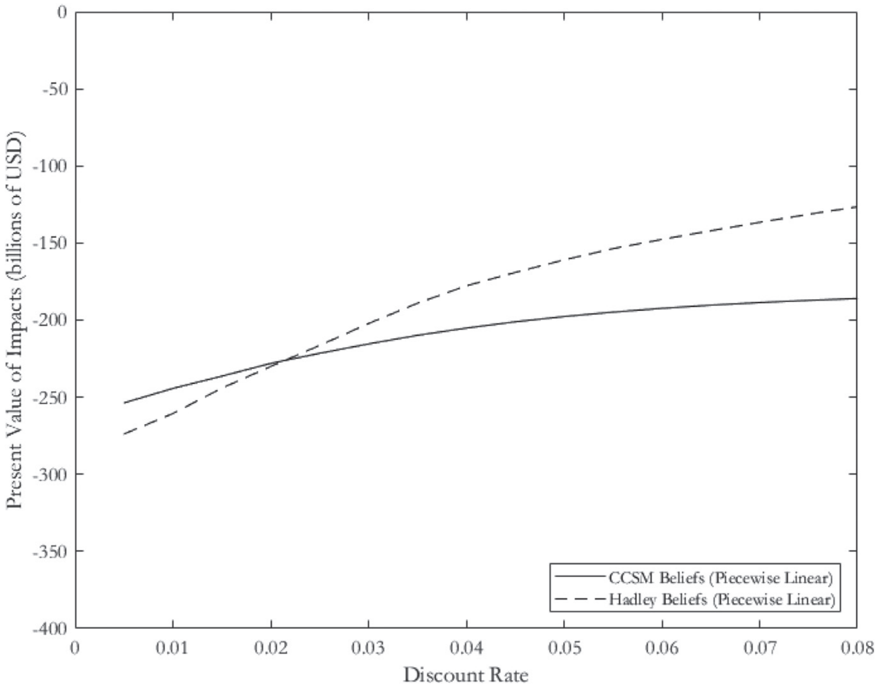

Fig. 2. Estimated present discounted value of estimated climate change impacts as a function of the discount rate.

6.3. Heterogeneity in public beliefs about climate change

There is substantial heterogeneity in the degree to which different economic agents assess the likelihood of climate change. Even among rural farmers in the US Midwest, there is variation in opinions over the likelihood of severe climate change and its causes (Arbuckle et al., 2013). Such differences could confound our estimates if these perceptions are correlated with the mean path of climate evolution. The existence of heterogeneity also suggests an additional test of our hypothesis that land markets capitalize future climate expectations: land values in counties where climate change is thought to be more likely should reflect future climate forecasts more strongly than in counties where beliefs in the likelihood of climate change are weaker.

To this end, we again estimate Equation (16), but now incorporate the estimated percentage of each county's population who think that 'global warming is happening' (using the Howe et al. (2015) terminology).[29] We incorporate this variable in two ways. First, we include it as a linear predictor of land values in the vector X. This provides a simple test of whether climate change perceptions are correlated with land prices. Second, we allow the parameter ω to vary across counties as a function of the local level of belief in climate change. This amounts to interacting beliefs with climate levels:

$$\omega_i = \frac{1}{1 + \exp(\theta_0 + \theta_1 SCCH_i)}$$

where $SCCH_i$ denotes the share of each county's population who think that global warming is happening, taken from the Howe et al. (2015) data. If θ_1 is positive, then higher local perceived likelihood of climate change is associated with a lower value of the parameter ω and higher weighting on future climate, supporting our hypothesis.

Results from this analysis are shown in Table 4. All models include state fixed effects. Columns (1) and (4) reproduce columns (1c) and (2c) in Table 3 and restrict the market belief parameter ω to be same across all counties. Columns (2) and (5) maintain this restriction, but introduce the county-specific climate change perception (SCCH) as an additional predictor of land values. In both specifications, the coefficient on the share of population 'believing climate change is happening' is positive but statistically significant. The estimated market belief parameter ω are the same as in the baseline specification of columns (1) and (4). In columns (3) and (6) we consider specifications where local perceptions of the likelihood of climate change is added both as a main effect and as a variable that can affect the market belief parameter, as in the above equation. Specifically, we estimate the parameters θ_0 and θ_1 (in addition to the climate price gradient parameter vector b), and then construct predicted market beliefs as a function of SCCH (share of population 'believing climate change is happening'). These predicted values (and standard errors) are reported in the lower panel of Table 4 for low (SCCH = 45), mean (SCCH = 57.7), and high (SCCH = 76) perceptions of the

[29] The variable 'happening' in Howe et al. (2015).

Table 5
Evolution in estimated market belief parameters (ω), 1978–2007.

Market belief parameter (ω)	Beliefs based on CCSM 3 A2		Beliefs based on Hadley 3 A2	
	(1a)	(1b)	(2a)	(2b)
1978	0.58***	(0.15)	0.44**	(0.14)
1982	0.59***	(0.14)	0.49***	(0.12)
1987	0.58***	(0.13)	0.48***	(0.12)
1992	0.43**	(0.14)	0.33**	(0.12)
1997	0.37**	(0.11)	0.27**	(0.09)
2002	0.14	(0.11)	0.07	(0.09)
2007	0	–	0	–
F-statistic testing parameter equality	2.40		2.17	
[p-value]	[0.056]		[0.079]	

Notes: The estimated market belief parameters are from a pooled regression for 1978–2007 data that includes year and state fixed effects and a piecwise linear function of the constructed future climate expectation index (see Equation 17). Standard errors are clustered on state. Asterisks denote p-value < 0.05 (*), <0.01 (**), <0.001 (***). See the text for more details on the other control variables included in the regressions.

likelihood that climate change is happening.[30] In both the (3) and (6) specifications, there is a clear inverse relationship between the predicted market belief parameter ω and the county-level perception of climate change. Counties where climate change is perceived as a low likelihood (SCCH = 45) have large estimates of ω in the 0.77–0.81 range, while counties where climate change is perceived as a high likelihood (SCCH = 76) have estimates of ω equal to 0.14 (and statistically indistinguishable from 0). This evidence suggests that land values in counties with higher population shares believing that climate change is happening are priced with a higher weight on climate forecasts (represented empirically by the Hadley and CCSM forecast indices) as opposed to historical climate.

6.4. Evolution of climate change beliefs over time

Using data on land values, county agricultural characteristics, and climate indices from prior years, we explore the evolution of the market belief parameter over time. This approach provides a simple specification test of the assumptions of our model and its empirical credibility. A priori, we expect that the market belief for the 'No change' scenario (ω) will grow larger as it is estimated from older data when public information on the prospects of climate change was not as widespread. In other words, we expect the estimate of ω for 2007 to be smaller than the corresponding estimate for 1978 (reflecting a stronger market belief in the likelihood of climate change in 2007 than in 1978).

We estimate an augmented version of regression Equation (16), but pool the data from 1978 to 2007 and include year fixed effects:

$$P_{ist} = \alpha_t + \widehat{Y}'_{is}(\omega_t)b + X'_{ist}\xi + \gamma_s + \varepsilon_{ist} \tag{17}$$

The market belief parameter ω_t is permitted to vary over time; all other parameters are restricted to be the same across periods (with the exception of year fixed effects); some covariates are time-varying. The constructed climate belief indices $Y(\omega)$ are constructed in the same manner as Equation (15), with the exception that indices for earlier periods are discounted back to the relevant year (e.g., the indices for 1978 are discounted to 1978).

Table 5 reports the coefficient estimates for the market belief parameters, when beliefs are constructed from the CCSM (columns 1a and 1b) and Hadley (columns 2a and 2b) data. The F-statistics at the bottom of the table test the equality of the market belief parameters over the period 1978–2007, excluding any values of ω that are on the boundary of [0, 1].[31] For both sets of constructed beliefs, the hypothesis of equality is rejected by the data at the 6% and 8% level, respectively. It is also evident that the patterns in the estimated parameters correspond to our intuition regarding the salience and public knowledge about ongoing climate change. In earlier years, ω is larger, and as time moves forward, ω decreases as the market incorporates the greater threat and likelihood of climate change. Overall, this simple test also supports our working hypothesis about the land market incorporating more information over time about expected future climate change in pricing agricultural land.

7. Conclusion

A fundamental underpinning of capital asset theory is that anticipated changes in future benefits associated with an asset will be capitalized into its current price. This key insight is routinely applied in hedonic regressions designed to value non-market

[30] Note that our measure of climate change beliefs (SCCH) is generated from from a multilevel regression model. Using a generated regressor results in consistent coefficient estimates but inconsistent estimates of coefficient standard errors (Pagan, 1984; Murphy and Topel, 1985). Conducting inference based on these standard errors generally leads to over-rejection of the null hypothesis. We do not adjust for this source of error because we do not have data corresponding to the 'first stage', and instead advise caution in performing inference from these regressions.

[31] This renders the statistical tests of equality conservative.

attributes in order to assess the impact of expected future changes. For example, climate can affect agricultural land values, zoning regulations can affect housing markets, and financial or workplace regulations can affect a company's valuation.

The canonical application uses historical data to estimate the response of asset prices to exogenous variation in a variable of interest that is expected to change in the future. Given an empirical estimate of the relationship between asset values and the variable of interest, it is straightforward to predict the costs or benefits associated with expected future changes in this variable. This approach has been applied across numerous economic assets in many sectors, and reported in hundreds of papers. The primary purpose of this paper is to show that the empirical component of this approach to economic valuation contains a fundamental assumption that is unlikely to hold in today's information-rich society. The implicit assumption is that the market is completely ignorant of the future change that is now anticipated by the analyst. We propose and test a straightforward correction that allows current asset markets to capitalize expectations about future climate change.

In climate change applications, scientists often predict increasing temperatures and changing precipitation patterns, but all empirical applications of the Ricardian method in the literature implicitly assume that current land markets ignore these predictions. While this assumption was quite plausible in the 1980s and 1990s, it is reasonable to wonder whether land markets are starting to account for publicly available climate forecasts. Ignoring this possibility leads to bias in the standard Ricardian regression. We derive the direction and magnitude of the bias, and show how it can be corrected. The direction and magnitude of the bias turns out to hinge on the correlation between past and future states and on the variances of those states. The bias can be positive, negative, or (in very special cases) zero.

We find clear evidence that current agricultural land markets already capitalize expectations about future climate: Future climate indices derived from climate predictions from the Hadley 3 and CCSM 3 global circulation models are shown to be important predictors of current land values, conditional on historical climate indices, state fixed effects, soil characteristics, and other predictors of farmland values typically used in standard application of the Ricardian method. Thus, while the theoretical points we derive here are relevant whether or not current markets already capitalize future climate, we have also shown that this effect may already be unfolding across the United States. Our simple empirical illustration indeed suggests that ignoring the capitalization of future climate expectations in the Ricardian method may lead us to overestimate climate damages by about 50%. Overall we view the evidence reported in this paper as strongly consistent with the hypothesis that land markets are forward looking and view our paper as a first step in what we hope will be a fruitful line of future research. In particular, we acknowledge that the evidence presented here is not fully definitive and warrants more research. Future research should attempt to leverage quasi-experimental variation (due to, for example, unanticipated information shocks) in order to identify the effects of expected climate change on current land markets.

Appendix A. Supplementary data

Supplementary data related to this article can be found at https://doi.org/10.1016/j.jeem.2018.03.009.

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